Improved Accuracy of Accelerated 3D T2* Mapping through Coherent Parallel Maximum Likelihood Estimation

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November 2, 2017

Synopsis

We propose an approach that can reconstruct isotropic T2* Maps from undersampled data with improved accuracy by utilizing the phase information. Our approach extends the acceleration attained in Parallel Imaging(PI) to Maximum Likelihood Estimation(MLE) by imposing the exponential relaxation directly in the complex signal domain. The method was tested on a Multiecho Gradient Echo(MEGE) T2* mapping experiment in a numerical phantom and a human brain with realtime (prospective) undersampling. The approach showed that incorporating the phase information to perform coherent fitting resulted in better denoising and improved accuracy of the parametric maps.

Word Count=720

1 Purpose

The quantification of tissue parameters from MRI datasets is emerging as a powerful tool for tissue characterization. The utilization of the technique in clinical scenarios is limited due to lengthy acquisition time. In recent years, research has focused on accelerating the acquisition by using techniques based on model-based reconstruction [1] [2] , dictionary [3] and sparsity [4] based methods. In all these previous works, magnitude images are utilized for the exponential fitting and the phase is discarded. To our knowledge, no previous work has explored the potential of coherent fitting using the phase information in accelerated data. However, the emerging Magnetic Resonance Fingerprinting (MRF) automatically works on the coherent signals [5]. Imposing exponential relaxation directly in the complex signal domain can be valuable for extending the acceleration attained by Parallel Imaging (PI). To our knowledge, no previous work has explored the potential of using coherent information in the exponential fitting in accelerated data. The purpose of this study is to ascertain the role of phase in improving the accuracy of the accelerated T2* mapping as compared to the magnitude only approaches.

2 Theory

For the MEGE Imaging sequence, the recorded complex signal is related to the tissue parameters (θ) as:

$$x \approx f(\theta) \tag{1}$$

where $\theta = (\rho, T2^*, \varphi_0, b)$ which is modulated by exponential relaxation given by:

$$f(\theta) = \rho\, exp^{(-t/T2^*)+j.(\varphi_0 - 2\pi bt)} \tag{2}$$

where ρ is the spin density of hydrogen atoms, t is the echo time (TE), $T2^*$ is the spin-spin relaxation time, b denotes the frequency shift in Hz and φ_0 is the constant phase due to multichannel coils. The off-resonance frequency b is caused by the field inhomogeneities which can be related to the system e.g eddy currents or biological e.g. at the tissue-air interface.

Given the above data model and noise characteristics, the reconstruction problem can be formulated assuming complex Gaussian noise as the following regularized ML estimation problem:

$$\arg\min_x \sum_{i=1}^{C}\sum_{n=1}^{N} \|y_{i,n} - Ex_n\|^2 + \lambda\|x_n - f(\theta)\|^2 \tag{3}$$

where $y_{i,n}$ is the acquired k-space data from the ith coil and nth echo, E is the encoding matrix, x is the image to be recovered, C is the total number of coils, N is the number of echoes and λ is the regularization parameter. The optimization is done iteratively using the alternating minimization with the details found in Figure (1).

Algorithm 1: Iterative MLE with Coherent Phase Fitting

Data: y= k-space measurement
initialization $x^{(0)}$=Initialized by SENSE ;
Optional Parameters; TolDiff= Reconstruction error between two iterations(default=$10e^{-4}$);
for *l=1; l:=l+1 or TolDIff* **do**
  Step1;
  $x^l = (E^H E + \lambda Id)^{-1}(E^H y^l + \lambda f(\theta^l))$;
  Step2 ;
  $\theta^{l+1} = \arg\min_\theta \|x^l - f(\theta^l)\|^2$;
end
Result: $\theta = T2^*, \rho, \varphi_0, b$

3 Methods

The proposed approach was tested on an anatomical brain phantom available from the BrainWeb Simulated Brain Database [6] and a healthy human brain. The in-vivo data was collected with an 8 channel head coil on a 1.5T clinical scanner (GE Healthcare, Waukesha, WI, USA). The data set was acquired using a 3D-enhanced fast gradient-recalled echo sequence with the following parameters (8 echoes, TR=67 ms, FOV= 156mm, 160 slices, readout Bandwidth=13.56 KHz, flip angle 15, 1.3 mm slice thickness). In addition to the fully

sampled scans, undersampled datasets were acquired prospectively for different acceleration factors(R=2,3,4,5,6). The undersampled datasets were acquired using Poisson Disk mask [7]. T2 * maps were reconstructed using both the magnitude only and the coherent phase fitting and compared with the fully sampled T2* Maps. The schematic diagram for the reconstruction using the method is shown in Figure (2). 3D coregistration and reslicing was applied using Statistical Parametric Mapping(spm-http://www.fil.ion.ucl.ac.uk/spm) to account for motion between the scans. Root Mean Squared Error(RMSE) was calculated between fully sampled and accelerated datasets to quantify the performance of the proposed method.

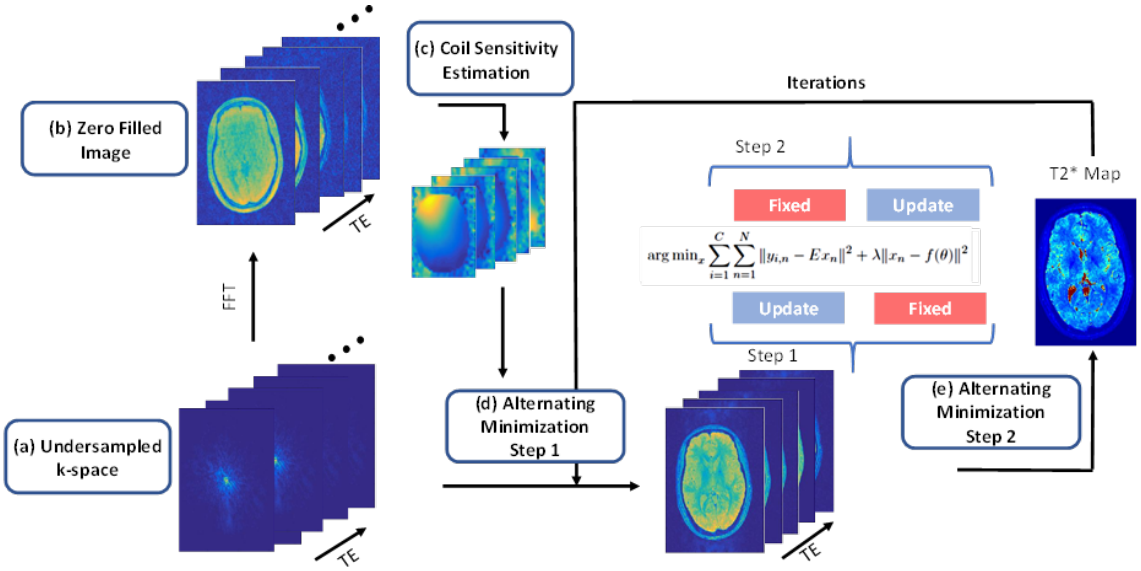

Figure 1: Schematic flowchart of the image reconstruction method a) undersampled k space data b) Zero filled image using FFT c) Sensitivity Maps are estimated d) Using the sensitivity Maps images the cost function is minimized by Alternating Minimization e) T2* Maps are reconstructed and the output is used for the Step 1 in an iterative manner.

4 Results

T2* maps obtained from the fully sampled data and the maps from undersampled data for the Numerical Phantom Figure 3(a & b) healthy volunteer Figure 4(a & b) with the magnitude and the complex data. The RMSE with respect to the fully sampled map is given below each map. The results show that the coherent fitting method tends to work well with less error(approx. 20 % better) as compared to magnitude only. T2* estimation using magnitude result in underestimation of the T2* values which is more evident in higher acceleration factors Figure (5).

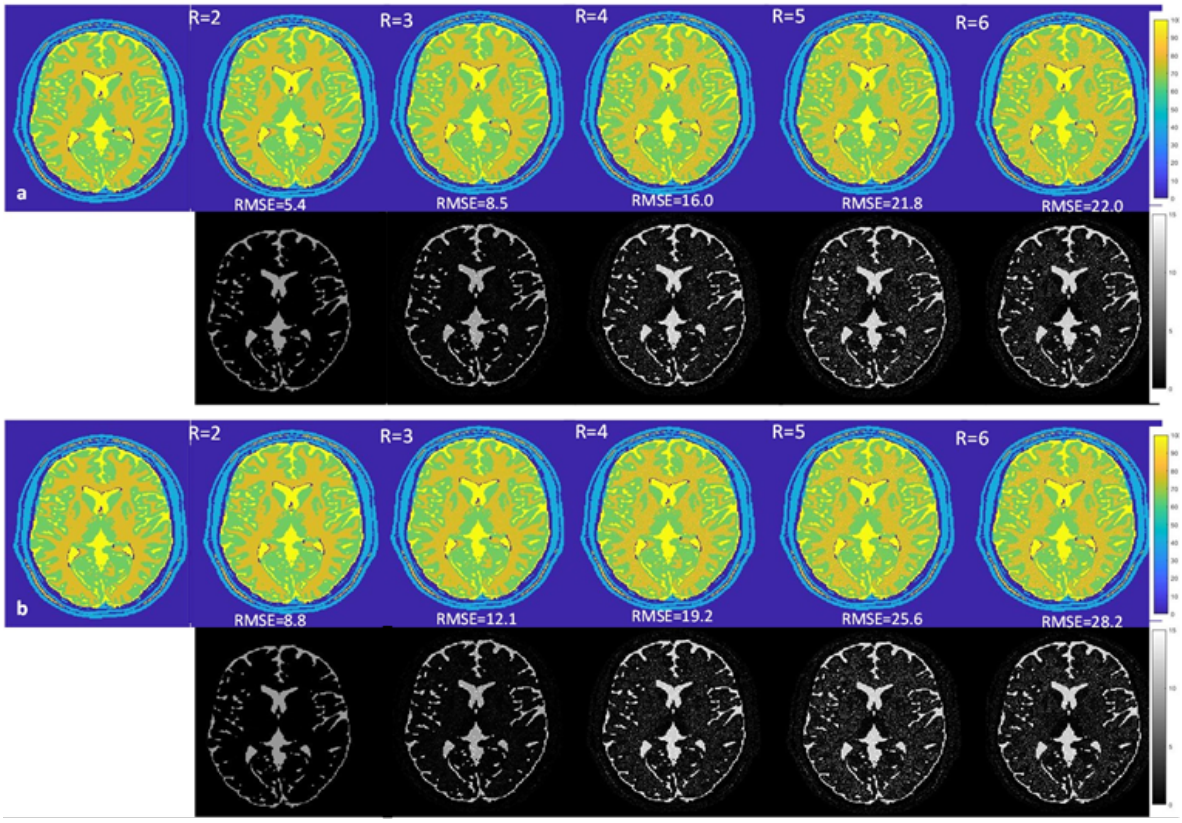

Figure 2: (a) T2* maps of the fully sampled and undersampled datasets of brain numerical phantom reconstructed with (a) coherent phase fitting (b) Magnitude. are shown in the top row. The corresponding difference of the T2* maps between fully sampled and the undersampled data are shown in the bottom row with the RMSE. The colorbar shows the T2* values in ms.

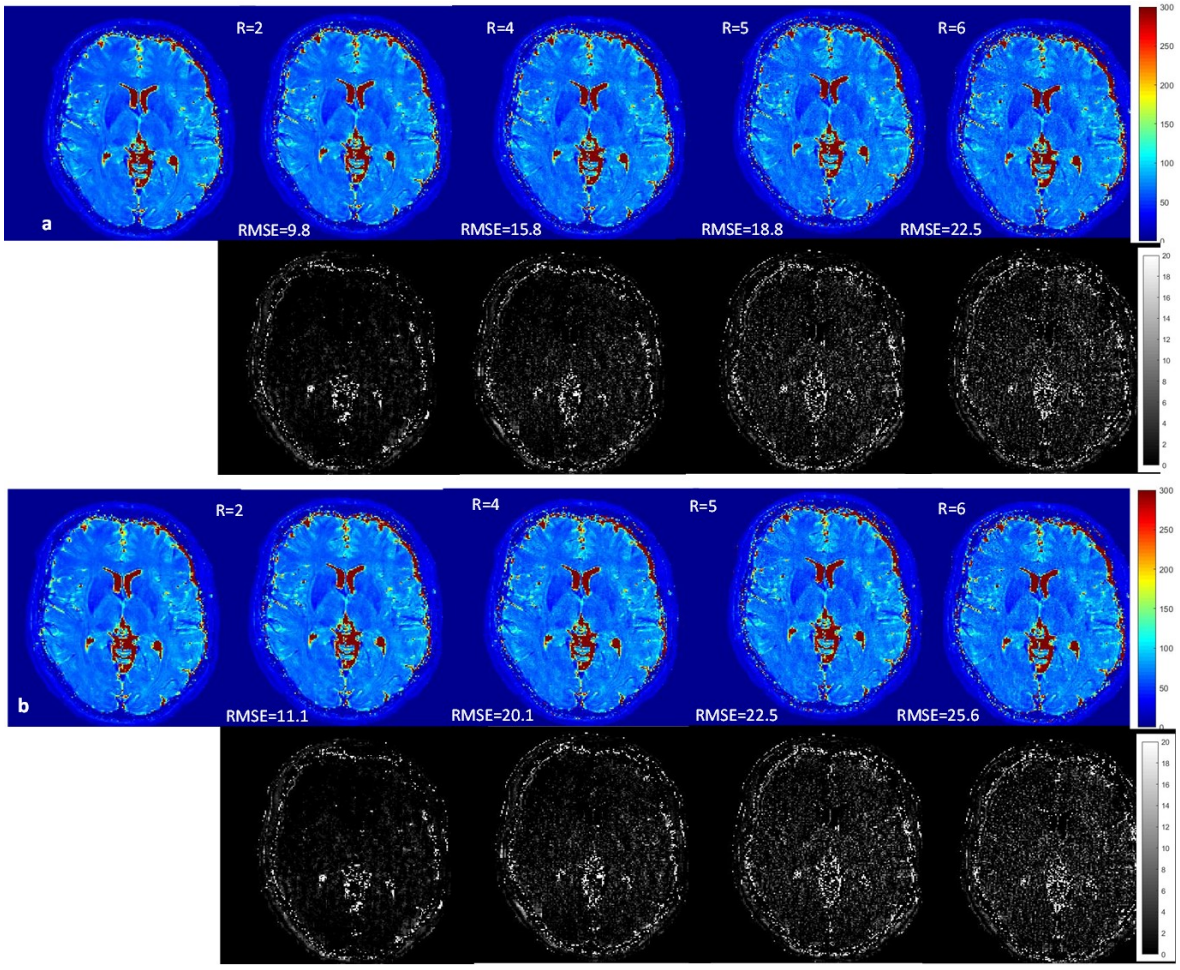

Figure 3: (a) T2* maps of the fully sampled dataset of healthy volunteer reconstructed with (a) coherent phase fitting (b) Magnitude are shown in the top row. The corresponding difference of the T2* maps between fully sampled and the undersampled data are shown in the bottom row with the RMSE. The colorbar shows the T2* values in ms.

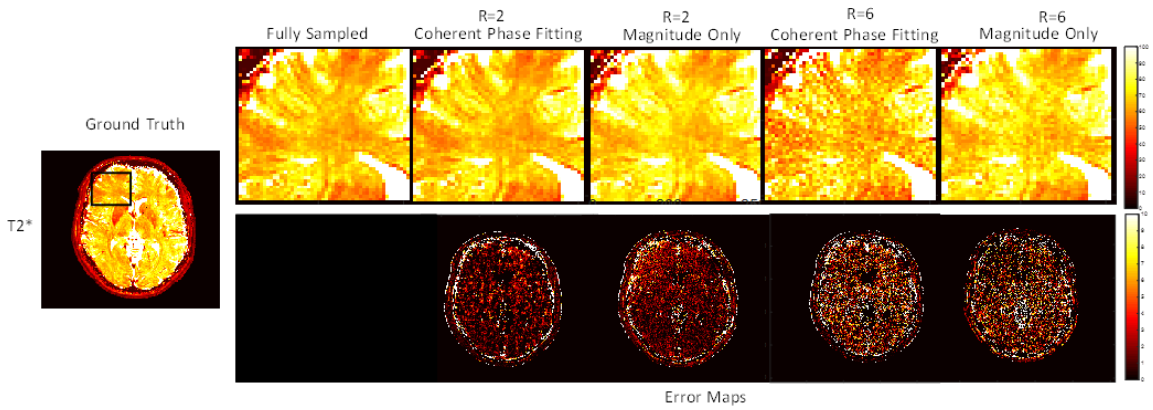

Figure 4: T2* maps of the fully sampled and the undersampled data for R=2 and R=6 with coherent phase fitting and magnitude only. For R=2, the T2* maps using coherent phase fitting shows better T2* estimation as compared to magnitude. For R=6, the T2* maps shows increased noise in both cases but the magnitude only results in under-estimation of T2* values

5 Discussion & Conclusion

We propose a method that can reconstruct T2* maps from undersampled data by combining the multicoil information with the coherent phase fitting. With the use of phase information, the accuracy of the T2* maps increased and additional information about the field inhomogeneity can be obtained. The total acquisition time of the 3D fully sampled data is 21 mins whereas for the accelerated scan with 6 times undersampling takes 4:29 mins. The implementation of this approach on the scanner will help in utilizing the technique in clinical scenarios.

Acknowledgment

The research leading to these results has received funding from the European Union's Seventh Framework Programme (FP7-PEOPLE-2013-ITN) under grant agreement n 607290 SpaRTaN. The work was carried out on a 1.5 T GE Signa clinical scanner operating within the Brain Research Imaging Centre (BRIC), Edinburgh Imaging, University of Edinburgh.

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